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Research Article

Exploring Consumer Preferences for Toyota Used Cars Through Machine Learning and Big Data

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ABSTRACT

The used car market has grown significantly worldwide, especially in developing countries were affordability and economic constraints shape consumer behavior. This study investigates how external factors, including brand image, corporate image, country image, and perceived risk, influence consumers' attitudes toward purchasing and their purchase intentions for used cars. To achieve each research objective, a dual-method approach was adopted. First, big data analysis and machine learning techniques were used to identify frequently purchased car brands and market trends. Second, a quantitative survey of 501 consumers was conducted to empirically examine the effects of selected external variables on buying behavior. The findings reveal that all five factors significantly influence consumer decisions, with brand image and corporate image having the most substantial direct impact on purchase attitude towards used cars. Moreover, perceived risk was found to moderate the relationship between attitude and purchase intention, suggesting that higher perceived risk weakens the positive influence of favorable attitudes on actual buying intentions. By combining big data analytics with survey-based research, this study offers a comprehensive and evidence-based perspective. The insights are valuable for marketers and importers seeking data-driven strategies in Mongolia's expanding used car sector.

Keywords: brand image, corporate image, country image, perceived risk, purchase attitude, purchase decision.

INTRODUCTION

In recent years, the global trade of used cars has expanded rapidly, driving demand for more accurate valuation and a deeper understanding of consumer decision-making in the used car market. Despite being more affordable than new vehicles, used cars continue to represent a high-involvement and high-cost purchase, particularly in developing countries, where consumers are often more financially constrained. In such contexts, including Mongolia, consumers not only evaluate the vehicle's current condition but also consider future resale value. As a result, many consumers tend to avoid vehicles that depreciate rapidly and instead show a preference for models known for value retention over time [32]. This behavior reflects a risk-averse attitude shaped by both individual financial limitations and broader macroeconomic conditions.

A combination of internal and external factors influences the decision to purchase a used vehicle. Internal factors are tangible attributes of the vehicle, such as age, mileage, engine performance, and fuel type, that consumers can directly evaluate. External factors, on the other hand, encompass broader market perceptions, including brand image, manufacturer reputation, and country of origin. These external elements significantly shape consumer trust and perception, especially in high-involvement product categories like automobiles [25], [43]. Together, both internal and external factors interact to influence consumer preferences, combining practical evaluations with emotional and psychological associations.

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In the Mongolian automobile market, where more than 500,000 vehicles, primarily from over ten international manufacturers, are in circulation, understanding consumer behavior is particularly important. Since the country lacks domestic car production, nearly 88% of all vehicles are imported as used cars, most of which have been in operation for over ten years by the time they enter the country, while only around 12% are brand new imports [42]. This market structure has shaped purchasing decisions that go beyond performance and price.

Today's consumers also weigh factors such as perceived risk, long-term value retention, expected resale price, and the ease of resale, which are particularly relevant in the context of secondhand markets. Amid these evolving market dynamics, big data analytics has emerged as a powerful tool in marketing and consumer behavior research. By analyzing massive and complex datasets, researchers are now able to uncover behavioral patterns with greater accuracy and predictive insight [2], [20]. This shift toward data-driven analysis has revolutionized the study of consumer preferences, enabling more context-specific and evidence-based insights [9]. As a result, a growing number of scholars have adopted oversized data methods to understand real-time market shifts and inform strategic decision-making.

Previous studies have primarily focused on the internal attributes of used vehicles, such as age and engine specifications. However, this study aims to investigate the role of external factors in shaping consumer decisions, with a particular focus on Toyota-branded vehicles, which dominate Mongolia's used car market. Moreover, this research adopts a dual-method approach that sets it apart from earlier works. First, it employs big data and machine learning techniques to identify which used car brands and manufacturers are most frequently purchased. Second, it incorporates a quantitative survey-based method to determine which vehicle attributes are prioritized by consumers during their decision-making process. By combining these two approaches, the study offers a more holistic and empirically grounded understanding of purchasing behavior in the used car sector [50]. Ultimately, the findings of this study hold practical implications for both individual consumers and automotive businesses. By identifying dominant purchasing patterns and key influencing factors, the research contributes to more data-driven strategies in vehicle marketing, pricing, and inventory management within Mongolia's automotive sector.

Also, the current work contributes to prior work on the effects of political orientations in consumption domains. Researchers have attended the significance of individuals' political orientations as a potent predictor for a wide range of product and brand preferences [24], [27]. Our work extends this line of research by examining how consumers' political orientation can shape their attitudes toward AI-based services. Our work also provides practical recommendations on which customer sociodemographic segment is better to target for a smoother launch of AI-based services and how marketers can alleviate algorithm aversion that some consumers may experience.

CONCEPTUAL BACKGROUND

1. Corporate Image

Corporate image refers to consumer perceptions, emotions, attitudes, beliefs, evaluations, and impressions about the company, depending on their direct or indirect interactions [45]. A strong corporate image evolves into an essential condition for the achievement of a solid and viable business [39]. It influences how consumers perceive and relate to a brand. According to [36], corporate image is an impact of attitude, which alters consumer perception and purchase intention. Building on this, [11] emphasized that corporate image is an essential marketing element that companies must prioritize. Similarly, [5] described corporate image as the person's overall perception of the company, encompassing the company's various attributes. Previous research indicates that corporate image has a significant effect on purchase behavior [19], [29], [4].

2. Brand Image

Brand image is a marketing factor that significantly influences consumers. Furthermore, brand image has been considered an essential concept in marketing since the 1950s, and it is a vital component of brand knowledge, particularly in the context of product branding [18]. Therefore, brand image is a crucial factor in business success, and marketers strive to preserve and elevate their brand image [34]. [3] found that brand image had a significant and positive impact on consumers' decisions when purchasing cars. Similarly, previous studies [21], [33], [6], [34] demonstrated that the brand image of automobiles significantly influences consumer purchase decisions and behavior. These findings propose that automotive companies with a favorable brand image can directly affect consumer behavior.

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3. Country Image

The concept of country image has received significant attention in global marketing research, especially its influence on consumer behavior. Each country has a distinct image that considerably influences consumer preferences and intentions toward products linked with that country [17]. Also, [7] stated that a country's image as a factor encompasses the evaluation of its national economy, political system, workforce training and competencies, and technological advancement. According to [18], country image is a country-specific factor that affects consumers' perceptions and attitudes towards products originating from that country. [15] observed that consumers' perceptions of a country's image significantly influence the purchase attitude, especially in developing countries. [34] proposed that the country in which the product is manufactured or assembled influences consumers' perceptions of product quality and purchasing intentions. Similar findings were reported by [31], who found that country image influences consumer purchase intention for electric vehicles.

4. Perceived Risk

Perceived risk, a consumer psychological factor, reflects the possibility of loss to them and impacts their attitude and reaction [28]. Perceived risk demonstrates a consumer's opinion about the probability and degree of adverse outcomes or loss from using a product. For technology-based products, perceived risks are complex and require a new conceptual framework [13]. Similarly, [49] explained that perceived risks represent a type of ambiguity for the future and express the psychological cost on consumers' purchasing behavior. Moreover, [35] proposed that perceived risk is a single construct, encompassing no distinct types of risks. According to [32], perceived risk is a valuable context that explains purchasing behavior. Their study found that it has a negative influence on purchase behavior. Similar conclusions were reached by [23], who found that consumers' perceived risk moderates the link between attitude and purchase intention.

5. Attitude

Numerous consumer behavior studies have been conducted using TPB and TRA theories to examine relationships between attitudes and purchase intentions. For instance, [10] posited that consumer attitude is a mixture of their beliefs, feelings, and behavioral intentions towards specific products and demonstrated its influence on the final decisions of consumers in marketing campaigns. Attitude is a consumer's internal feeling of favorability or unfavorability toward a product [47]. According to [30], attitude toward a specific country refers to whether the judgment of the country is favorable or unfavorable. Furthermore, the attitude includes not only cognitive but also affective and conative factors, including purchase intent. The attitude of consumers is an essential aspect that is significantly correlated with their purchasing intentions [43]. Similarly, the more positive the consumer's attitude toward the product, the higher the consumer's intentions to purchase [14].

6. Purchase intention

Intention refers to a person's scheme or tendency to engage in specific behavior, such as incorporating a product or service [12]. Purchase intention refers to a consumer's attitude toward a specific buying process, reflecting their willingness to buy a product. Various external and internal factors also influence it and are an indicator of consumer buying behavior [51]. Comparably, [18] view intention of purchase as an indicator of a consumer's behavioral inclination to buy products and as crucial for the actual purchasing decision. Moreover, [46] defined consumers' purchase intentions for automobiles as an individual's evaluation of willingness to perform certain purchases. Previous studies [44], [38], [22] revealed that attitude has a positive influence on purchase intention for automobiles.

Research Model and Hypotheses

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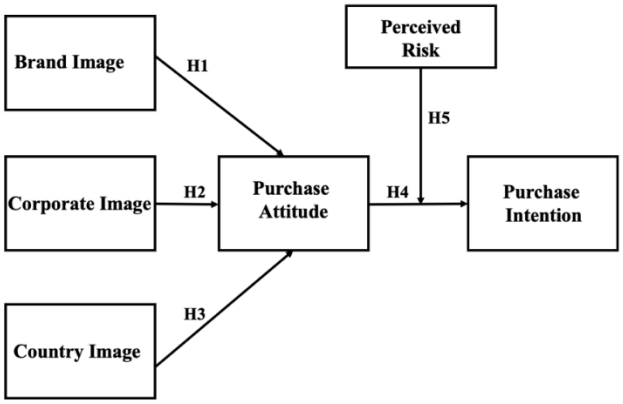

H1: Brand image positively and significantly influences consumers' purchase attitude.
H2: Corporate image positively and significantly influences consumers' purchase attitude.
H3: Country image positively and significantly influences consumers' purchase attitude.
H4: Consumers' purchase attitude positively influences their purchase intention.
H5: Consumers' perceived risk will moderate the relationship between purchase attitude and purchase intention.

RESEARCH METHODOLY

This study adopts a two-phase mixed-method research design that combines big data analytics with quantitative analysis using Structural Equation Modeling (SEM) to investigate both the pricing mechanisms of used cars and the behavioral factors influencing consumer purchase decisions.

In the first phase, a big data analysis was performed using a dataset of 82,898 used car listings posted on the Mongolian online marketplace [41] between September 2024 and March 2025. The dataset included 17 key features such as price, brand, model, engine capacity, year of manufacture, mileage, gearbox type, and other vehicle characteristics. To assess the influence of these variables on car pricing, ensemble machine learning models including Decision Tree, Random Forest, Gradient Boosting, XGBoost, LightGBM, HistGradientBoosting, and Extra Trees were implemented. The performance of these models was evaluated based on MAE, MSE, and R^2 scores. Model training and tuning were performed using an 80:20 train-test split along with 10-fold cross-validation for robustness.

In the second phase, a quantitative survey was conducted among 501 used car consumers selected through simple random sampling. The study aimed to explore how external factors, such as brand image, manufacturer reputation, and country of origin, affect consumer preferences and decision-making. The collected data were analyzed using Structural Equation Modeling (SEM), which allows for the testing of complex relationships among observed and latent variables. SEM was chosen due to its ability to validate theoretical constructs and examine causal relationships within the proposed research framework.

By integrating big data techniques with survey-based SEM analysis, this study combines predictive analytics with theory-driven validation, offering a more comprehensive understanding of consumer behavior and pricing trends in Mongolia's used car market. This dual-method approach distinguishes the present study from earlier research that typically employed only one methodological approach.

Additionally, a non-linear model was used to evaluate the depreciation of vehicle value over time for popular brands, especially Toyota models such as Prius, Lexus, Land Cruiser, Harrier, and Crown, which are among the most frequently sold. This modeling was based on the median annual price of used Toyota and other major brand vehicles manufactured between 2001 and 2024. Using the median price helped to filter out the influence of outlier listings with extremely high or low prices, enabling a more accurate estimation of value change in the market. Moreover, by using the coefficients of this model, depreciation was modeled in cumulative percentage terms over specific year intervals based on the year of manufacture. This approach provides a data-driven foundation for consumer decision-making regarding the sale, purchase, and usage planning of used vehicles, offering practical and reliable insights grounded in quantitative analysis.

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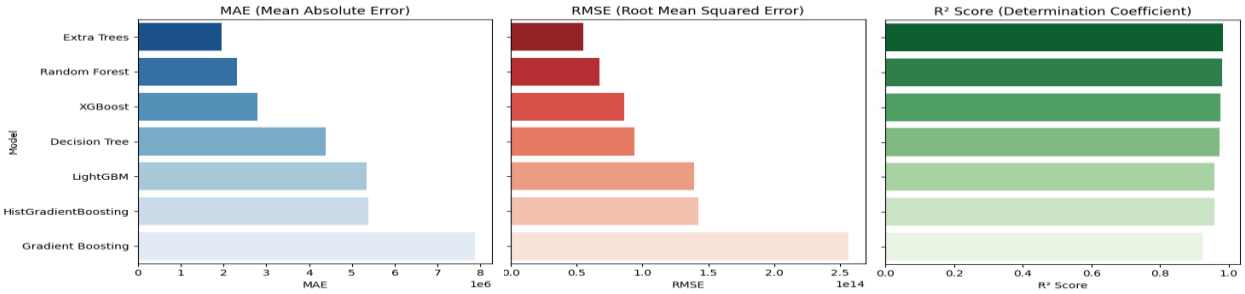
RESULTS

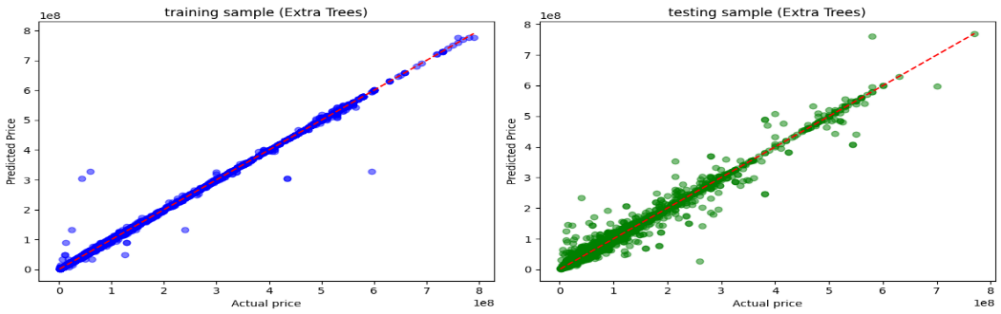
Among the 82,898 used cars included in the study, 97% belonged to six major brands: Toyota (88.7%), Subaru (2.1%), Mercedes-Benz (2.0%), Nissan (1.6%), Hyundai (1.3%), and Mitsubishi (1.2%). Within the Toyota brand, 76.5% of vehicles were from specific models, namely Prius (38.0%), Lexus (15.2%), Land Cruiser (8.4%), Harrier (8.4%), and Crown (6.5%). This indicates that in the Mongolian used car market, Toyota models such as Prius, Lexus, and Land Cruiser enjoy the highest demand among consumers, likely due to factors such as brand reputation and perceived quality. Among the 17 variables influencing car prices, year of manufacture, engine capacity, model, and brand demonstrated the highest explanatory power, accounting for approximately 90% of the variance in price. Conversely, variables such as gearbox, number of seats (gate), and leasing availability had minimal impact on the price valuation model, suggesting they did not significantly contribute to explaining price variation. Furthermore, correlation analysis among variables showed that all pairwise correlations had an absolute value of less than 0.5 ($|r| < 0.5$), indicating no multicollinearity issues. Ensemble machine learning methods were applied to analyze the factors affecting used car prices. Model performance was compared using MAE, RMSE, and R^2 scores, with the Extra Trees model achieving the highest accuracy (MAE = 1.98, RMSE = 5.69×10^{13}, R^2 = 0.9830) (Fig. 1). Other models also demonstrated strong explanatory power, with R^2 scores as follows: Random Forest (97.9%), XGBoost (97.4%), Decision Tree (97.3%), LightGBM (95.8%), HistGradientBoosting (95.7%), and Gradient Boosting (92.3%). All models achieved over 90% explanatory power, indicating that machine learning, notably the Extra Trees algorithm, is highly suitable for predicting used car prices in the Mongolian market.

Figure 1. Performance Comparison of Machine Learning Models in Car Price Estimation



The comparison between actual and predicted prices using the Extra Trees model, which demonstrated the best statistical significance, shows that the model effectively learns from both training and test datasets, producing highly accurate predictions in Figure 2. This confirms that the Extra Trees model can reliably and with relatively low error forecast used car prices.

Figure 2. Relationship Between Actual and Predicted Prices Using Extra Trees Model: Training vs Testing Samples



To evaluate how vehicle depreciation varies depending on the year of manufacture using non-linear models, the median prices of all cars produced between 2001 and 2024 were utilized (Fig 3). Among the models tested, the quadratic trend model demonstrated the best statistical significance, achieving an R-squared value of 0.974.

$$Log(Price) = 19.4815696911 - 0.221820921076 * \text{Time} + 0.00430758956172 * Time^2$$

t-Statistic	204.4398	-12.62996	6.315886

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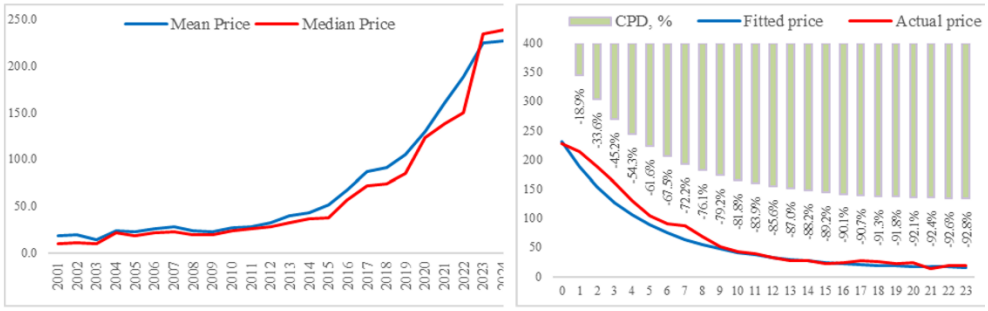
The model results indicate that the depreciation of used car values has a non-linear relationship with the year of manufacture. Analysis of price dynamics from 2001 to 2024 shows that both average and median car prices exhibited a steady upward trend, with a particularly sharp increase observed since 2017. This surge may be associated with factors such as domestic inflation, economic growth, and currency exchange rates. Regarding cumulative price depreciation (CPD) over time and the residuals between actual and predicted prices, the data reveal that car values drop sharply within the first 5 to 10 years after manufacture, decreasing on average by approximately 54% to 60% after 10 years. Beyond this period, the rate of depreciation slows, stabilizing around 92.8% after 20 years. The minimal difference between predicted and actual prices further confirms the model's strong performance and high statistical significance.

Figure 3. Car Price Trend and Depreciation Curve



Mean and median price, million MNT Cumulative price-decrease, by time

The rate of depreciation in vehicle value based on the year of manufacture varies across different brands. In other words, the dynamics of car value depreciation are influenced not only by the age of the vehicle but also by factors such as the specific brand, model, and quality.

Table 1. Price depreciation model results by brand

		LOG(TOY)	LOG(SUB)	LOG(MER)	LOG(NIS)	LOG(HYU)	LOG(MITS)
C	Coefficient	19.75579	18.46493	20.63901	19.01220	19.01780	18.35221
	t-Statistic	234.8481	122.8316	137.1706	117.1761	127.0933	167.7319
Time	Coefficient	-0.243905	-0.145098	-0.258511	-0.194188	-0.236957	-0.089913
	t-Statistic	-15.73156	-5.236995	-9.322005	-6.493618	-8.591899	-11.74202
$Time^2$	Coefficient	0.005027	0.002109	0.004541	0.002566	0.004161	
	t-Statistic	8.349100	1.959959	4.217162	2.209815	3.885474	
Adjusted R-squared		0.979130	0.894575	0.955258	0.935153	0.947736	0.856138
S.E. of regression		0.126081	0.225310	0.225513	0.243185	0.224275	0.259674
F-statistic		540.5237	98.58267	246.5321	166.8415	209.5355	137.8751

The survey was conducted between April and May 2025. The sample size of 501 participants is statistically adequate for the analyses performed. The sample was drawn from a diverse demographic group, including different age ranges and income levels, to ensure that it represents the broader population of car owners in developing countries. Given the rapid number of used car owners in Mongolia, this sample is expected to provide valuable insights into consumer

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behavior in similar markets. Additionally, the study used self-reported data, which may introduce response bias. Participants may overestimate or underestimate their behaviors and attitudes, and these factors may affect the validity of the data. The demographic variables of participants presented in Table 2 show that the participants were predominantly female (59.5%) and within the 29-39 age group (46.7%). Additionally, a significant portion of the participants had a monthly household income ranging from 2,000,000 to 3,000,000 MNT (36.7%).

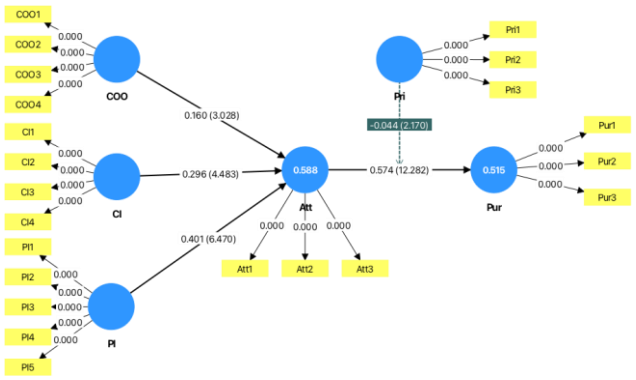
Table 2. Demographic information of participants

Variables	Data	Number	Percentage (%)
Gender	Men	203	40.5%
	Women	298	59.5%
Age	18-29	112	22.4%
	29-39	234	46.7%
	39-49	99	19.8%
	50-59	49	9.8%
	Over 60	7	1.4%
Household income (MNT)	Up to 1.000.000	58	11.6%
	1.000.001-2.000.000	123	24.6%
	2.000.001-3.000.000	184	36.7%
	3.000.001-4.000.000	74	14.8%
	Over 4.000.000	62	12.4%
TOTAL		501	100

Data analysis procedure

The researchers analyzed the data using IBM SPSS 27 and Smart PLS 4 social science statistical software programs. Structural equation modeling (SEM) has become a popular statistical tool in a variety of disciplines. Among the different structural equation modeling approaches, the partial least squares (PLS) method has gained significant attention due to its ability to handle complex models, non-normal data, and small sample sizes [16]. Specifically, researchers utilized the Smart PLS 4 software for hypothesis testing purposes, while the SPSS software was employed to conduct descriptive analysis and data screening tasks. When the emphasis is on prediction and theory building, partial least squares (PLS) analysis is the favored approach since its statistical power is always greater than or equal to that of Covariance-Based Structural Equation Modeling (CBSEM) [37].

Figure 4. Smart PLS, t-test results



Measurement model

The study employed a range of statistical methods to assess the reliability and validity of the measurement model. Composite reliability, a measure of internal consistency, was measured and found to exceed the suggested level of

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0.80, with values ranging from 0.880 to 0.935. Furthermore, Cronbach's alpha, which measures a scale's internal consistency, was greater than the recommended 0.876, suggesting a high level of dependability. The results show the stability and consistency of the measures [8]. Furthermore, the average variance retrieved, which represents the entire variation in the indicators accounted for by the latent construct, was much greater than the intended 0.50 threshold, indicating strong convergent validity [1]. Overall, the findings suggest that the study methodology is acceptable, and the measures are accurate and trustworthy, as demonstrated by Cronbach's alpha and composite reliability values of more than 0.70. Tables 3 provide details on the measurement model results.

Table 3. The output of the measurement model

Paths	Cronbach's alpha	CR (rho_a)	CR (rho_c)	(AVE)
Purchase attitude	0.892	0.893	0.933	0.823
Corporate image	0.905	0.910	0.933	0.778
COO	0.902	0.903	0.932	0.773
Product image	0.911	0.917	0.934	0.738
Price perception	0.876	0.880	0.924	0.801
Purchase intention	0.933	0.935	0.957	0.882

This research investigated the stated hypotheses using structural model path coefficients at a significant level. The path coefficients were found to be statistically significant based on the calculated t-statistics. As expected, brand image was positively associated with their attitude towards the car (β=0.401, t=6.470, p<.000). Thus, the first hypothesis (H1) was accepted. The corporate image of the car manufacturer was found to positively impact consumers' attitudes (β=0.296, t=4.483, p<.000). Consequently, the second hypothesis (H2) was accepted. Moreover, research results show that the country image had a positive and significant effect on purchase attitude towards used cars (β=0.160, t=3.028, p<.000). Therefore, (H3) was supported.

Furthermore, the research revealed that consumers' attitudes towards cars had a positive and significant effect on their purchase intentions for cars (β=0.574, t=12.282, p<0.00). Therefore, the fourth hypothesis (H4) was also accepted.

Table 4: Path coefficient results

Paths	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
Attitude -> Purchase	0.574	0.574	0.047	12.282	0.000
CI -> Attitude	0.296	0.295	0.066	4.483	0.000
COO -> Attitude	0.160	0.161	0.053	3.028	0.002
PI -> Attitude	0.401	0.399	0.062	6.470	0.000
Pri -> Purchase	0.166	0.167	0.04	4.132	0.000
R2					0.515
R2 adjustment					0.516

Moderator analysis in PLS-SEM can help researchers understand how the strength or direction of the relationship between two variables, such as attitude and purchase intention, may be influenced by a third variable. The second purpose of this research paper is to test the moderation effect of price perception. The study examined the role of price perception in the relationships between attitude and purchase intention. Therefore, the researchers aimed to investigate how price perception moderates the relationship between attitude and purchase intention towards a car. In order to examine the moderating role of price perception, the product indicator approach was employed, which involved multiplying the attitude variable by the moderating variable of price perception, as shown in Table 5.

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According to the research results, price perception moderates the relationship between attitude and purchase intention. Therefore, the hypothesis (H5) is supported.

Table 5. Moderation analysis results

Paths	Original sample	S.D.	t-statistic	p-value	Findings
Price x attitude -> Purchase	-0.044	0.043	0.02	2.17	Moderated

DISCUSSION

This study adopts a dual-method approach to examine consumer behavior in Mongolia's used car market comprehensively. The primary objective was to develop an empirical pricing model using big data and machine learning techniques to estimate vehicle depreciation based on real-market listing data. The secondary objective was to investigate how external image-related factors—brand image, corporate image, and country image influence consumer attitudes and intentions toward purchasing used vehicles, particularly Toyota, and how perceived risk moderates this relationship.

Findings from the machine learning component reveal that vehicle age exerts a non-linear but significant influence on price depreciation, and that depreciation rates vary markedly by brand and model. For example, Toyota models were shown to retain value more effectively over time, suggesting a link between brand quality perceptions and long-term asset value. The Extra Trees algorithm outperformed other models, demonstrating minimal error between predicted and actual prices. This high level of predictive accuracy supports the model's potential applications in real-world contexts such as asset valuation for banks, insurance pricing, and informed consumer decision-making.

The machine learning models, notably the high-performing Extra Trees algorithm, demonstrated that certain brands, such as Toyota, retain value more effectively over time, with lower depreciation rates even after extended use. These insights confirm that consumers are more likely to purchase vehicles that are perceived to depreciate slowly, which is consistent with the idea that perceived risk (e.g., fear of rapid value loss or resale difficulty) influences the strength of their purchase intentions.

Furthermore, the predictive accuracy of the pricing model strengthens the practical relevance of this study, suggesting that data-driven tools can help reduce perceived risk by offering transparent, evidence-based valuation. This reinforces the role of objective price information in mitigating the uncertainty consumers face in used car markets.

The secondary objective of this study was to examine consumers' intentions toward used vehicles, particularly Toyota, in Mongolia. To achieve this, three key antecedents were explored: brand image, corporate image, and country image, and their effects on consumers' attitudes toward purchasing used Toyota vehicles.

The findings robustly support Hypothesis 1 (H1), indicating that brand image, as a composite of product attributes and perceived quality, is a well-documented determinant of consumer decision-making [26]. By explicitly referencing product-specific attributes (e.g., vehicle age, engine capacity, safety, comfort), the sentence underscores their role in shaping attitudes, consistent with studies on product involvement and perceived quality in the automotive industry [48]. These results highlight the critical role of product-specific attributes in fostering positive consumer attitudes, aligning with established consumer behavior theories.

Hypothesis 2 (H2) is also supported, confirming that corporate image has a significant direct impact on consumers' purchase attitudes. This aligns with prior research suggesting that perceptions of the manufacturer's credibility, social responsibility, and service quality positively influence consumer evaluations [36]. Corporate image, as a multidimensional construct, includes credibility, social responsibility, and service quality, which prior studies [36] have shown to enhance consumer trust and favorable evaluations. In the used car market, where uncertainty and risk are high, a manufacturer's reputation for reliability and ethical practices can significantly shape purchase decisions. This result extends the literature by highlighting the direct effect of corporate image on attitudes, suggesting that manufacturers should prioritize corporate social responsibility and service quality to foster consumer trust. The reference to [36] is retained to anchor the findings in prior research, while the broader implication emphasizes the strategic importance of corporate image in high-involvement purchase contexts.

The findings substantiate Hypothesis 3 (H3), demonstrating that country image significantly shapes consumers' purchase attitudes in the used car market. This result aligns with prior research [18], which highlights that consumers' perceptions of a country's quality and reliability foster positive attitudes toward its products. Specifically, in developing markets such as Mongolia, these findings corroborate [15] emphasis on the pivotal role of country image in influencing consumer evaluations, underscoring its relevance in high-involvement purchase decisions. Theoretically, consumers use a country's image as a heuristic to evaluate product quality and reliability. Studies such as [31] and [18] demonstrate that positive country associations enhance consumer attitudes, particularly for products like automobiles, where quality perceptions are critical. The findings extend this literature by confirming the country image effect's applicability to the used car market, suggesting that manufacturers and marketers should leverage positive country associations in branding strategies to enhance consumer confidence.

Furthermore, Hypothesis 4 (H4) is supported, establishing a strong positive relationship between purchase attitude and purchase intention. This result reinforces previous studies suggesting that favorable attitudes toward vehicles directly enhance the likelihood of purchase [44], [38], [22].

Hypothesis 5 (H5) is supported by the findings, indicating that perceived risk significantly moderates the relationship between purchase attitude and purchase intention. Specifically, the data reveal that when perceived risk is high, the positive effect of a favorable purchase attitude on intention is weakened. In contrast, at lower levels of perceived risk, this relationship becomes stronger. This moderation effect suggests that even when consumers hold a positive attitude toward purchasing a used car, elevated perceptions of financial, functional, or performance-related risks, including concerns about high vehicle prices, can reduce their likelihood of buying a used car.

This finding is theoretically consistent with prior literature that positions perceived risk as a psychological barrier in the attitude-behavior pathway [40]. In the context of high-involvement purchases, such as automobiles, particularly in developing markets like Mongolia, uncertainty related to resale value, maintenance costs, hidden defects, and especially the high price of vehicles may lead to hesitation. Therefore, the presence of perceived risk dilutes the translation of attitude into behavioral intention. From a practical standpoint, this highlights the need for marketers and auto dealers to mitigate perceived risks, especially price-related concerns, through pricing strategies, financing options, vehicle warranties, and transparent product information, in order to strengthen the conversion from positive attitudes to actual purchase behavior. Overall, the findings of this study contribute to a deeper understanding of how external factors and perceived risk interact to influence consumer behavior in emerging used car markets.

The connection between the two studies is both theoretical and practical. The machine learning findings empirically confirm that brands with lower depreciation are likely to be perceived as less risky, which in turn strengthens purchase intention, validating the moderating effect of perceived risk identified in the behavioral study. Consumers appear to implicitly factor in depreciation trends and resale potential, favoring vehicles with substantial residual value. This suggests that risk aversion in high-involvement purchases like used cars is not only psychological but also informed by tangible market realities. Together, the dual findings provide a multidimensional understanding of consumer decision-making: while attitudes and perceptions shape intention at a psychological level, objective market data reinforces and validates those perceptions. This integration demonstrates the value of combining big data analytics with behavioral modeling in consumer research, offering both academic insights and actionable implications for automotive marketers, financial institutions, and policymakers operating in developing economies like Mongolia.

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